Using Position Extrema Points to Capture Shape in On-line Handwritten Signature Verification

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Abstract

There is considerable interest in authentication based on handwritten signature verification (HSV) because of the long–standing tradition of its use in many common authentication tasks. HSV may be considered superior to many other biometric authentication techniques, for example fingerprints or retinal patterns, which are more reliable but also more intrusive. Furthermore, they require special and relatively expensive hardware to capture the image. The present paper is an attempt to develop a reliable HSV technique by capturing the shape of the signature using the position extrema points of a signature. The technique presented essentially captures the directions of pen motion during the writing of the signature and this is represented in a simple way by a string. The technique is evaluated and shown to be promising.

Keywords

Handwritten signature verification, biometrics, authentication

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1 Introduction

In the modern society, there has been a vast increase in the number of documents that are being transmitted and stored electronically. Just like paper documents, and perhaps more, electronic documents are subject to forgery. This increasing dependence on electronic storage and transmission of documents has created a need for electronically verifying the identity of the sender. Handwritten signatures have been the normal and customary method of identity verification that has worked well over the years and there is an obvious need for computer verification of handwritten signatures.

It is well known that no two genuine signatures of a person are precisely the same and some signature experts note that if two signatures written on paper were the same they could be considered forgery by tracing. Successive signatures by the same person will differ, both globally and locally and may also differ in scale and orientation. Osborn [12] notes that the variations in signatures of a person are themselves habitual and are clearly shown in any collection of genuine signatures produced at different times and under a great variety of conditions. When carefully examined the signature will show running through them a marked, unmistakable individuality even in the manner in which they vary as compared with one another. Hilton [6] notes that once a person is used to signing his/her signature, the nerve impulses are controlled by the brain without any particular attention to detail. This is in contrast to normal handwriting, which relies on position and visual feedback during the writing. Signature writing is considered *ballistic motion*, which is rapid practised motion which is not driven by feedback but is predetermined by the brain and which cannot be done slowly.

The dynamics of the signature are captured by a graphics tablet in the data that is given by:

$$S(t) = [x(t), y(t), p(t)]^T \quad t = 0, 1, 2, \ldots, n$$

that is, it is a collection of x, y location values of the pen tip and pen tip pressure values usually at equal time intervals. Some devices also capture azimuth and attitude. Many tablets sample at the rate of 200 times a second and the resolution of such devices is often 1000 pixels/inch although some have finer resolution. Typical American signatures are a writing of the person's name and therefore for American signatures the x-values typically grow linearly with time with small oscillations on the linear curve while the y-values show a more oscillatory variation with time, becoming positive and negative many times during a signature. An example of x and y profiles of a signature is given in Figure 1. Note the three pen-ups in the profiles. The tablet used provided a resolution of 277 dots/inch and sampled at the rate of 200 samples per second.

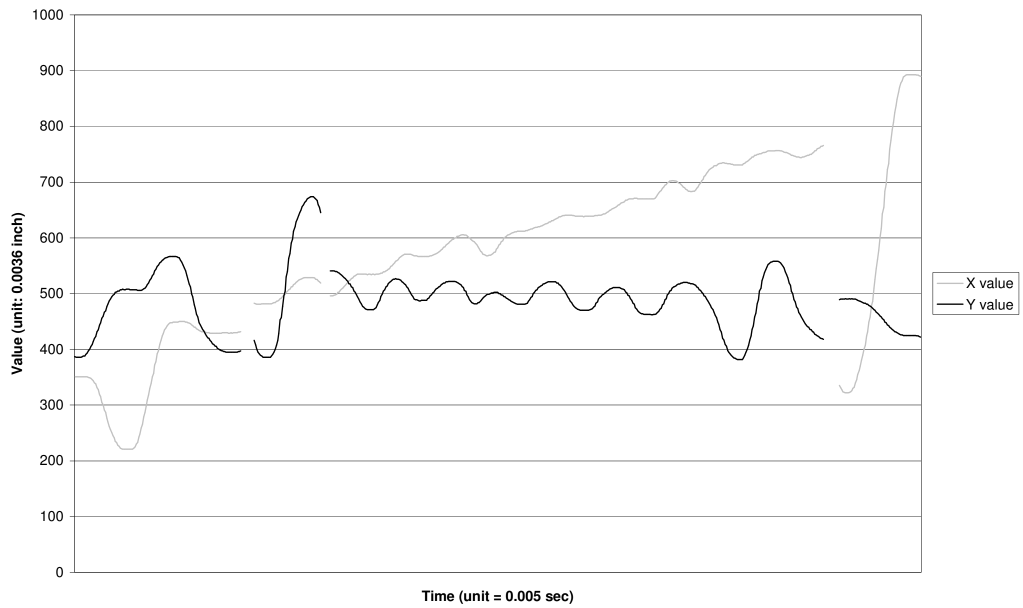

Figure 1. *x* and *y* profiles of a signature

Given the variation in genuine signatures of a person, every time a person signs his/her signature the number of samples obtained is somewhat different. This variation in genuine signatures of an individual makes it difficult to compare point-to-point one set of values from one genuine signature with a set from another.

Most HSV techniques use the following six–step procedure for performance evaluation:

1. Registration – Obtain a number of signatures for each individual at enrolment or registration time (these signatures are called *sample signatures* although other terms like *training signatures* have also been used).

2. Pre-processing and Building Reference Signature(s) – pre-process the sample signatures if required, compute the features required, and produce one or more reference signatures. Decide on what threshold will be used.
3. Test Signature – when a user wishes to be authenticated, he/she presents a signature (we call this signature the *test signature*). Compute the features of this signature.
4. Comparison Processing – the test signature is compared with the reference signature(s) based on the features' values and the difference between the two is then computed using one of the many existing (or specially developed) distance measures.
5. Performance Evaluation – for each signature that claims to be a genuine signature, compare the distance computed with the threshold decided in Step 2 above. If the difference between the two is smaller, accept the signature otherwise reject.
6. Repeat Steps 3-5 for the given set of genuine signatures and forgery attempts, compute the false rejection rate (FRR), the skilled false acceptance rate (FAR) and the random FAR.

Obtaining good estimates of FAR is very difficult, since actual forgeries are impossible to obtain. Performance evaluations therefore rely on two types of forged signatures. A forgery may be *skilled* if it is produced when the forger has had access to one or more genuine signatures for viewing and/or practice. A forgery is called *zero-effort* or *random* when either another person's genuine signature is used as a forgery or the forger has no access to the genuine signature and is either only given the name of the person whose signature is to be forged or just asked to sign any signature without even knowing the name. Random forgeries generally lead to much smaller FAR than skilled forgeries.

Many on-line signature verification techniques focus primarily on the dynamics of the signature and they ignore the shape since matching signature shape is difficult and good results can be obtained even if the shape is ignored. However highly reliable on-line signature verification techniques must, we believe, require consideration of the shape as well as the dynamics of the signature.

The present paper describes one approach to representing signature shape in on-line HSV.

The paper is organized as follows. We first present, in Section 2, a brief review of recent literature in the field of on-line HSV. Section 3 describes the proposed shape representation while Section 4 discusses performance evaluation. Section 5 discusses further work and concludes the paper.

2. Review of Some Earlier Work

Early HSV work is described by Herbst and Liu [5], Plamondon and Lorette [14], Leclerc and Plamondon [8] and Gupta and McCabe [4].

Two different approaches to signature verification are common. In the first approach, called the *functional approach*, all the collected position (or velocity or acceleration) values of the test and reference signatures are compared point-to-point, perhaps by computing a set of correlation coefficients between the two signatures. Such comparison may require signature segmentation and comparison of corresponding segments may require alignment. In the second approach, called the *parametric approach*, all the available values are not used. Instead, a number of global values, called *statistical features* or *parameters,* are computed and compared.

Nalwa [11] challenges the notion that the success of on-line HSV hinges on capturing velocities or forces during signature production. His approach is based on using jitter, aspect normalization, parameterization over normalized length, sliding computation window, center of mass, torque, moments of inertia, moving coordinate frame and saturation, weighted cross–correlation and warping. It is recommended that errors from different models be combined using the harmonic mean so that if one of the errors is low then the mean is low and the signature is verified.

Jitter is proposed since it is claimed that a person forging a signature is constantly correcting the pen trajectory to conform to an a priori curve. Aspect normalization is based on the observation that individuals do not scale their signatures equally along both x and y dimensions. Parameterization of a signature over its normalized arc-length is recommended as opposed to parameterization over time. Once parameterized, a sliding window is used to compute the following five characteristics of the signature over each window: center of mass (x and y coordinates of the center in the window), torque (twice the signed area, negative if clockwise, swept with respect to the origin by the portion of the signature within the window), and moments of inertia about the x-axis and y-axis within the window. Warping is now used in comparing the reference signatures with the test signature so that an overall error measure is minimized.

Three signature databases were used to test the proposed algorithm. Some genuine signatures and forgeries from the datasets were removed. The results from the three test databases and one that included all three, using 4, 5 and 6 reference signatures, are presented. Equal error rate (EER) was found to vary between 2 and 5.

Jain, Griess and Connell [7] present a system in which certain critical points, for example, start and end points of a stroke and points of trajectory change, are extracted for each signature before pre-processing. Signature samples are then resampled uniformly with equidistant spacing. Each signature is then transformed into one long stroke by concatenating all the strokes followed by smoothing. The original number of strokes is used as a global feature. Two types of local features, spatial and temporal, are extracted from the *x* and *y* coordinates before pre-processing. The spatial features are static features that relate to the shape of the signature. They are the *x* and *y* coordinate differences between two consecutive points, the absolute *y* coordinates with reference to the center of the signature, the sine and cosine of the angles with the *x*-axis, the curvature, and the grey values in a 9 x 9 pixel neighborhood. The temporal feature is the speed at local points as it was found to be very effective.

Local features of each signature are represented as a string and a modified string matching is used to find dissimilarity values. A penalty for differences in the number of strokes is included. In the verification process, a test signature is compared with each reference signature and the dissimilarity values are combined into one value. The proposed technique was tested using two datasets. The best error rates using a common threshold were 3.3% FRR and 2.7% FAR and the best error rates using writer-dependent thresholds were 2.8% FRR and 1.6% FAR. The FAR rates appear to be based on random forgeries. No FAR for skilled forgery was reported.

Feng and Wah [3] present a technique called extreme points warping (EPW), which uses dynamic time warping of selected important points (the peaks and valleys) of a signature. EPW involves first finding these points (the algorithm ignores small peaks and valleys), matching them and then warping the segments between them. The test results were encouraging but the error rates were quite high.

Ortega-Garcia et al. [13] present results of using the usual five time sequences, *x* and *y* coordinates, pressure, inclination and attitude as well as three derived sequences, path tangent angle, path velocity and log curvature radius. These eight sequences and their first and second derivatives make up 24 sequences at each sample point. Signatures are modeled using hidden Markov models (HMM) based on the sequences. The technique was tested using a signature database of 15 genuine signatures and 15 forgeries each from 50 people. The tests, using the same threshold for all, resulted in 4.83% EER which reduced to 0.98% by using user-specific thresholds.

Quan and Ji [15] define sixteen types of extrema points including eight maxima and minima in the *x* and *y* directions (they differentiate between an extreme point reached by clockwise motion of the pen and another reached by anticlockwise motion) and eight different combinations of maxima and minima (for example, two different points where both *x* maxima and *y* minima occur). These extrema are identified in the signature and some that are too close to other extrema are removed. The pattern for the test signature is then compared with that of the reference signature using derivative dynamic time warping. The distance between the two is computed. Six sample signatures for each signer were used to find a reference signature by comparing each of the six samples with the other five and counting the number of matching points. The signature with the largest total matching points was chosen as the reference. Using random forgeries, an EER of 3.8% was obtained.

3. A New Technique of Capturing On–line Signature Shape

We believe we need a signature shape representation technique that overcomes the problem posed by variations in the genuine signatures of a person. Although the variations for most people are not great, they can be quite significant for some people. The variations are perhaps worst for people that have more than one type of signature. Liu, Herbst and Anthony [9] found that in their experimentation with 248 users, three users continually varied between two signatures. Even when such dramatic variation is not present, signature variations are often significant enough to make point-to-point comparison even with dynamic time warping difficult.

We present a representation for signature shape that captures the essentials of the shape but allows considerable variation. The representation is related to the work of Ehrich and Foith [2], Lu [10] and Chen and Lu [1] for representing the shape of a waveform by a tree. Wave representation is relevant to signature verification since the x and y profiles (as in Figure 1), in spite of pen-up times, may be considered waveforms and may be represented by any of the tree representations cited above. We however do not follow the tree representation but instead adapt it to develop a more convenient string representation.

The technique proposed uses x and y profile extrema values to capture the essence of a signature's shape. It is best described using an example. Consider Figure 2 which shows the x and y profiles of a signature fragment of about one second, the full profiles are given in Figure 1. Before developing the signature representation, the local minima and maxima of both x and y profiles are identified. This may involve ignoring some minor maxima and minima because of jitter. Now the following symbols are used to label the extrema: A and B for local maxima and minima of the x profile, C and D for a local maxima and minima of the y profile and P for pen-up. The extrema of both profiles together and the pen-up events from left to right of the profiles in Figure 2 may be represented by the string ADBCABDPBCDCABDPBCADBC.

The representation presents some difficulty in labeling the end points of the strokes. We have used the convention that an end point on the left (right) will be considered minimum if the value is growing (increasing) after (before) it and maximum if the opposite is the case. Since both x and y end points are usually together, we have adopted the convention of putting the x extremum label before the y extremum label.

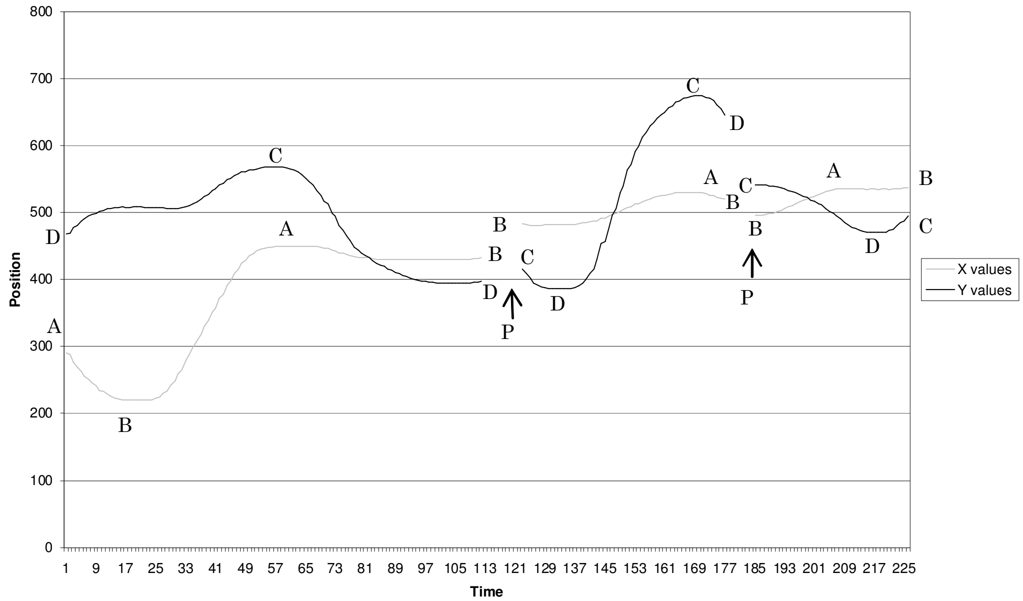

Figure 2. *x* and *y* profiles of a signature fragment
(Time and Position units are the same as in Figure 1)

Another way to look at this representation is to view it as a description of pen motion since the pen moving from the current position to the first quadrant will eventually lead to both *x* and *y* maxima (AC or CA), in the second quadrant to *x* minimum and *y* maximum (BC or CB) and similarly BD or DB in the third quadrant and AD or DA in the fourth. For example BCADB shows that the pen moved in the north-west direction, then the north-east direction, followed by south-east and south-west. The representation ignores the curvature or the size of the curves that BCADB describes and is a representation for many curves that look somewhat similar. Thus the representation provides considerable flexibility and tolerates considerable variation in the way the pen moves while capturing the shape as well as the direction of pen movement during signature writing. Given the flexible representation, similar strings should always be obtained for the genuine signatures of a person in spite of minor variations in them.

To test this technique, one or more reference signatures are needed. One approach would be to build a signature representation for each of the say five sample signatures and then combine them into one reference signature, but there is no simple technique to combine several different strings into one that is typical of all. A simple solution is to use all the sample signatures as reference signatures and to compare the test signature against each of them and obtain either the mean or the smallest distance. The basis of using the smallest distance is that the sample signatures provide a collection of signatures that show the habitual variations in a person's signature and the test signature should be compared with a reference signature closest to it.

To compare two signatures, the string representations of both are found and compared and distance between them is calculated. The distance so computed is now compared with the threshold and if lower the test signature is accepted.

4. Experimentation and Performance Evaluation

A number of experiments were conducted to evaluate the performance of the technique in Section 3 and a number of its variations. The following procedure based on earlier discussion was followed:

(a) Select five sample signatures randomly for each person from the given set of genuine signatures and find the string representation for each using the technique that is being evaluated.

(b) Compute the distance between each of the ten possible pairings of the sample signatures. Distance was computed using the algorithm of Wagner and Fischer (1974) as described below. Compute the mean and standard deviations of the distances.

(c) For each signature in the test database (other than the five sample signatures), find its string representation.

(d) Compare the test signature with each of the five reference signatures of the person. Compute the mean distance.

(e) Compare the distance computed in (d) with the mean computed in (b) plus the threshold times the standard deviation. If the test difference is smaller, accept the signature, otherwise reject.

(f) Repeat Steps (c) – (e) for the given set of genuine signatures and forgery attempts, compute the FRR, the skilled FAR and the random FAR.

The string distance algorithm of Wagner and Fischer (1974) uses a dynamic programming approach to successively evaluate the distance between longer and longer prefixes of the two strings from previous values until the final result is obtained. We briefly describe the algorithm.

Let the distance between the prefixes of strings x and y, of lengths i and j, respectively, be denoted by d_{ij} which is given by

$$d_{ij} = d(x(1,i), y(1,j))$$

Assuming the costs of a symbol substitution, $s(a \text{ with } b)$, symbol deletion, $d(a)$, and symbol insertion, $i(a)$, to be all equal to 1, the cost d_{ij} may be computed using the following recurrent formula:

$$d_{ij} = \min\{d_{i-1,j} + d(x_i),\ d_{i,j-1} + i(y_j),\ d_{ij} + s(x_i \text{ with } y_j)\}$$

We conducted experimentation using a signature database of 60 users which included 15 genuine signatures and 5 skilled forgeries for each. For each user, five signatures were selected randomly to be used as reference signatures and the remaining ten were used as test signatures. The results of the experiments are now described.

4.1 The Basic Technique

Experiment 1

In the first experiment, the performance of the basic technique presented in Section 3 was evaluated. As given in the last section, each signature was represented by a string of x and *y* profile extrema and pen-up events. Skilled forgeries EER of 14% and random forgeries EER of 7% was obtained.

Experiment 2

Disappointed by the results of Experiment 1, it was decided to include additional signature detail in the representation by including information about the magnitude of the extrema. Rather than representing extrema by A, B, C and D, extrema with large magnitudes (as measured from the last extreme point) were represented by two identical symbols (e.g. AA or BB) while low magnitudes were represented by a single symbol. This improved the results somewhat, skilled forgeries EER was close to 11% and random forgeries EER was down to 4.5%.

4.2 Combining Shape and Motion

Experiment 3

In this experiment some global features' information about the signature was used in addition to the extrema information. A two-step procedure using dynamic global features as well as the representation developed in the last section was designed and tested. The first stage consisted of using seven dynamic features (viz. total time, number of sign changes in the *x* and *y* velocities and *x* and *y* accelerations, pen-up time and the total path length). The second stage used the extrema representation described in the last section. Both stages used the same five reference signatures but employed different thresholds. The verification process consisted of passing both the first stage and the second stage successfully. The technique resulted in skilled forgeries EER of 7% and random forgeries EER of 4.4%.

Experiment 4

The three experiments above suggested that the representation of *x* and *y* extrema, even when used in combination with global features' information of the signature, was not sufficient to accurately verify a signature. A final modification of the basic scheme was now considered and evaluated.

This modification involved information about the length of time gaps between successive extrema included in the signature representation. The approach investigated was to use one or more symbols to represent the length of time gaps between successive extrema. In our view, it was not desirable to represent the time information accurately since flexibility to deal with variation in genuine signatures is required. Just a rough indication of the length of the gap in the signature representation was called for. Using different symbols for different time gaps was rejected since somewhat different time gaps in signature representations being compared would then result in a mismatch if the lengths were different. Multiple instances of the same symbol were used instead. It was necessary to ensure that the number of time gap symbols (say T) in the signature representation were not large as compared to the number of symbols that represented the signature extrema since the extrema are considered by this approach to be the important features of a signature. A time symbol T for each time gap of four pen samples was inserted in the signature representation. Therefore 10 pen samples between successive extrema resulted in TT being inserted between the two extrema symbols while 20 samples resulted in TTTTT being inserted. A typical signature representation of a signature was found to be more than 100 symbols long, including 2-3 P symbols, perhaps 20 T symbols and the remaining extrema symbols (A, B, C and D).

The results obtained are presented in Table 1. Skilled forgeries EER of 4.8% and random forgeries EER of 2.25% were now achieved.

Threshold	FRR	Skilled FAR	FRR + FAR	Random FAR
0.0	18.9%	0.0%	18.9%	0.0%
0.5	11.8%	0.6%	12.4%	0.1%
1.0	6.4%	4.0%	10.4%	0.6%
1.5	4.6%	4.9%	9.5%	1.4%
2.0	2.8%	6.2%	9.0%	2.6%

Table 1. Results of including length of time gaps information between successive extrema in the signature representation

4.3 Using Variable Thresholds

Experiment 5

The results in Table 1 were obtained by using the same predetermined threshold for each person. When individual thresholds were used, we were able to obtain skilled EER of 2.5% and random EER of 1.5%. We found that we could obtain EER of 0% for 90% of the individuals. For the remaining 10%, 0% EER was not possible and for one or two individuals a low error rate appeared impossible using the techniques described in this paper.

5. Conclusions and Further Work

We have presented a signature representation that captures the essentials of the signature shape and the way the pen moves during signature writing by using a string representation for the extrema of the x and y profiles of the signature as well as information about the length of time gaps between successive extrema. The proposed HSV technique is simple, attractive and flexible. The signature representation proposed is small enough (perhaps of the order of 100 bytes) to be stored on a credit card strip or embedded in a document for verification. We expect that some further improvements may be possible. An interesting conclusion of this study is that a very reliable algorithm for say 90% of the population may be possible but no current algorithm will perform at close to 0% EER for the whole population.

Although we have so far discussed a representation that combines information from the x and y profiles (as well as pen-up and time), the approach may be used to combine four or more different waves corresponding to a signature to arrive at one combined string representation. For example, it is possible to build a single representation for the extrema of a signature's x, y profiles, velocities profiles and accelerations profiles. We have not tried such a representation since in our experience we have found that often the simple techniques are the most effective.

A number of variations of the signature representation technique presented above are possible. For example, it may be worthwhile to consider the following:

1. Can we improve on the current string representation and the string matching algorithm?
2. In Experiment 2 we included some information about extrema magnitudes. Further work may be required to more effectively represent magnitude in the signature representation. What should be the granularity of magnitude information if it is to be included?

3. The proposed signature representation implicitly records information about the pen direction of motion. Would it be more effective to explicitly include further information about the direction, perhaps as suggested by Quan and Ji [15]?
4. Is it possible to design a more effective two-stage HSV technique similar to that employed in Experiment 3?

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